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GENETIC ANTENNA OPTIMIZATION:
A TALE OF TWO CHROMOSOMES

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Abstract: In this paper, we describe how to apply genetic algorithm (GA) optimization techniques to two diverse antenna optimization problems: electrically-small bent-wire antennas and a digital ionosonde transmit antenna. For each of these we present a description of the problem and one or more ways in which it can be modeled for genetic algorithm optimization. The goal of this paper is not to present optimal results for each of these antenna design areas, but rather to illustrate how antenna optimization problems can be translated into chromosome representations for genetic algorithm optimization. Lessons learned from using different chromosome representations are presented, along with simulated and measured results as available.

1. Introduction

Genetic algorithms (GAs) have been demonstrated as a useful tool for both designing and optimizing many different types of antennas, ranging from electrically small antennas to loaded monopoles and ultra wide-band antennas. [1,2,3,4,5,6]. However, it is not always clear how to translate one's antenna problem into a representation suitable for genetic optimization. This can be a major drawback towards the greater use of genetic algorithms for antenna design or optimization. ˙

We differentiate the terms *genetic antenna design* and *optimization* as follows. In **genetic antenna design**, it is not necessary to have a pre-conceived notion as to the basic antenna shape. We start with a set of parameters that this shape must lie

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within and the materials that make up the antenna. The final shape and design of the antenna may vary widely, depending on the chromosome representation and how the genetic algorithm progresses. In some genetic algorithm designs, we may converge to a new nonintuitive antenna shape; in others, the GA continually reaches a well-known existing antenna design.

In *genetic antenna optimization*, we attempt to optimize the parameters of an existing antenna design for a particular electromagnetic environment to obtain the best customization of that design for the particular conditions of the problem. The role of the genetic algorithm in this case is searching through the parameters within that antenna design to find a good or optimal solution that meets our particular criteria.

We have shown in [6] that the genetic representation itself is key to how well a genetic algorithm can optimize a problem. Different representations yield different subsets of possible solutions, some of which are more-general than others. A good representation will allow for a large portion of the function space to be explored. A poor genetic representation will limit the type of antenna which may be expressed and only allow for pieces of space of all possible solutions to be explored. In this latter case, the solution found by the genetic algorithm may not truly be the optimal solution to the problem, but only the optimal answer which can be expressed by this chromosome representation.

In this paper, we illustrate chromosome representations for two very different types of antenna designs and optimizations. In the first, we revisit the problem of electrically-small bent-wire genetic antenna design and illustrate how different antenna models and chromosome designs affect convergence to an optimized solution. In the second, we explore genetic algorithm optimization of a hybrid digital ionosonde transmit antenna having a more complicated figure of merit. While we present simulated and measured results as currently available, the goal of this paper is not to present optimal results for each of these antenna types, but rather to illustrate how antenna optimization problems can be translated into a GA chromosome representation. In our discussion, we present lessons-learned in translation to chromosome representation and the limits inherent in these representations.

2. Genetic Algorithm Overview

A full discussion of genetic algorithms (GAs) is well beyond the scope of this paper; however, we present a limited overview here for the reader's benefit. The

literature abounds with many detailed discussions of simple and competent genetic algorithms; an excellent resource can be found in [7].

The genetic antenna designs and optimizations presented in this paper are created using what is known as a *simple* genetic algorithm, shown in Fig. 1. This is the type most widely used in the literature and what is generally thought of as a genetic algorithm.
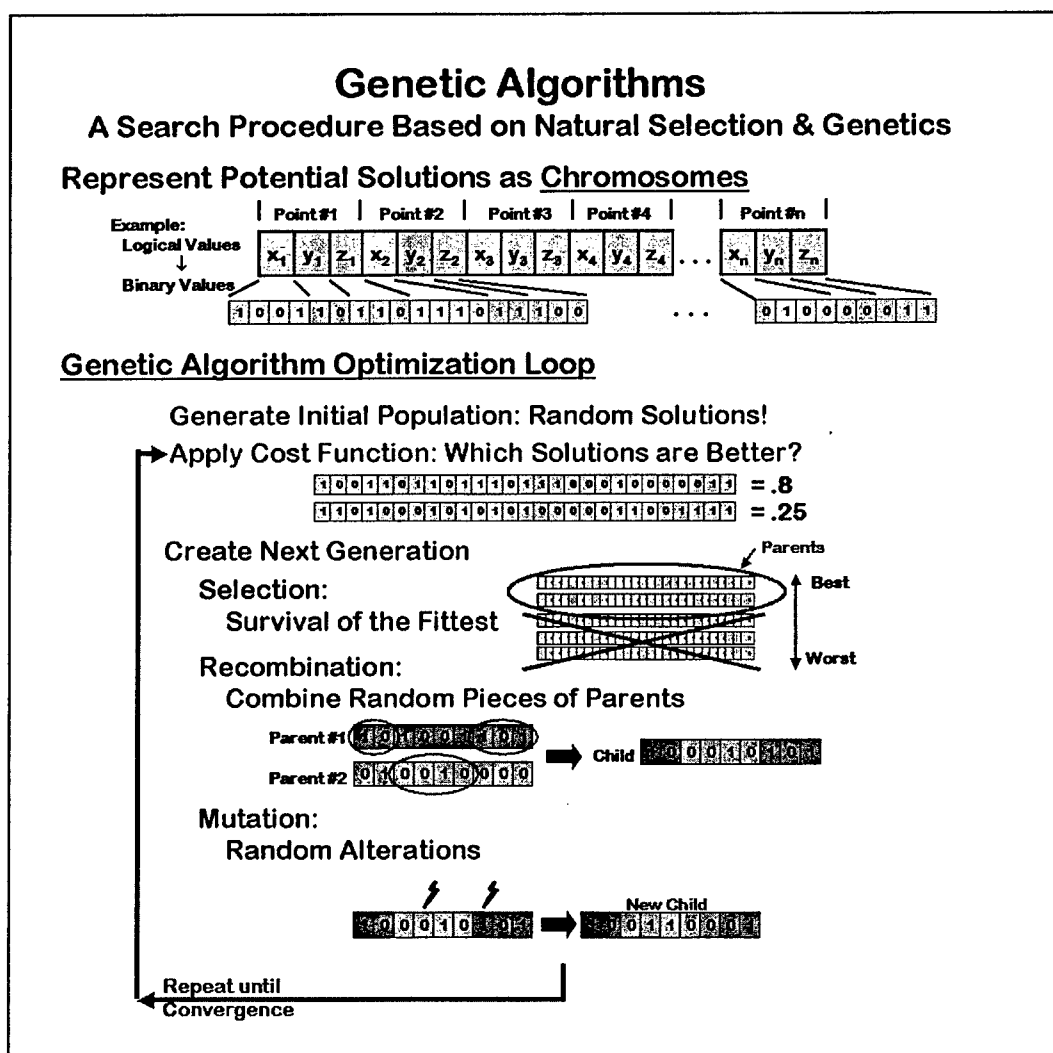

Figure 1: Genetic algorithm overview. After determining a chromosome representation and developing a cost function, the genetic algorithm optimization loop is applied until convergence occurs.

First, a *chromosome* is designed to encode potential problem solutions, usually as a string of binary values. A *cost function* is developed so that different solutions may be compared against each other to determine which are better. After these are both developed, the genetic algorithm begins with an initial (usually random) *population*. The solutions represented by the population are evaluated and ranked using the cost function to determine which are better. Good parents are *selected* and then used in *recombination* to create children, which then have some probability of *mutation*. After mutation, the next population is evaluated and ranked. The process continues until an acceptable solution is found or convergence occurs (solutions do not continue to improve).

The simple operations of selection, recombination, and mutation act to combine pieces of salient information (called *schema)* from multiple "good" solutions together. Chromosomes with some of these good schema should perform better than other chromosomes without them and therefore be selected as parents. Through recombination, good schema representing different parts of a "good" solution have the chance of occurring simultaneously within the same chromosome to create an even better solution. Mutations allow for small changes to occur in the schema and new genetic material to be introduced which may not be present in the initial population.

Over time, we would like the GA to generate a chromosome which contains all the best schema and which represents the best possible solution to the problem. In a simple GA, that sometimes happens. Other times, especially in multi-modal problems, the GA converges prematurely to a non-optimal solution which represents a local minimum. Depending on the problem, the solution represented by one of these local minima might still be quite acceptable as an antenna solution; however, one should be careful about declaring this to be an optimal solution to the problem.

To help a simple GA work effectively, *it is important to encode one's chromosome so that pieces of schema which relate strongly to each other, such as those representing a certain physical characteristic of the solution, be somewhat close together in the chromosome.* This increases the probability that these schema will cross-over together during recombination[4]. In the following two examples, you will note our chromosomes have been developed with this principal in mind to allow the simple genetic algorithm to work as effectively as possible.

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[4] Note that this is not so critical in competent GAs [7], where genes within a chromosome may be reordered dynamically or linked together to make sure that schema which are relevant to each other stick together during recombination.

3. Electrically Small Bent-Wire Antenna Optimization

The crooked wire genetic antenna design problem was first introduced by Altshuler and Linden [5] and the electrically-small bent wire antenna subsequently pursued by Altshuler in [1]. In this latter problem, the genetic algorithm was used to design new shapes of electrically small bent wire antennas. The goal of the genetic algorithm was to determine the lowest VSWR obtainable for a single wire antenna matched to 50Ω and fitting within a given physical cube size. Other constraints were that the antenna consisted of only a single wire and that pieces of the antenna within the cube could not touch the ground plane nor each other.

3.1 Coordinate Chromosome Representation

One method of encoding this antenna design for a genetic algorithm represents the antenna as a fixed number of straight wire segments connected in series at their

Chromosome: Genes represent wire endpoints.
Gene: a floating point number (0-1 inclusive)
x_n, y_n, z_n, **are pseudo-coordinates**
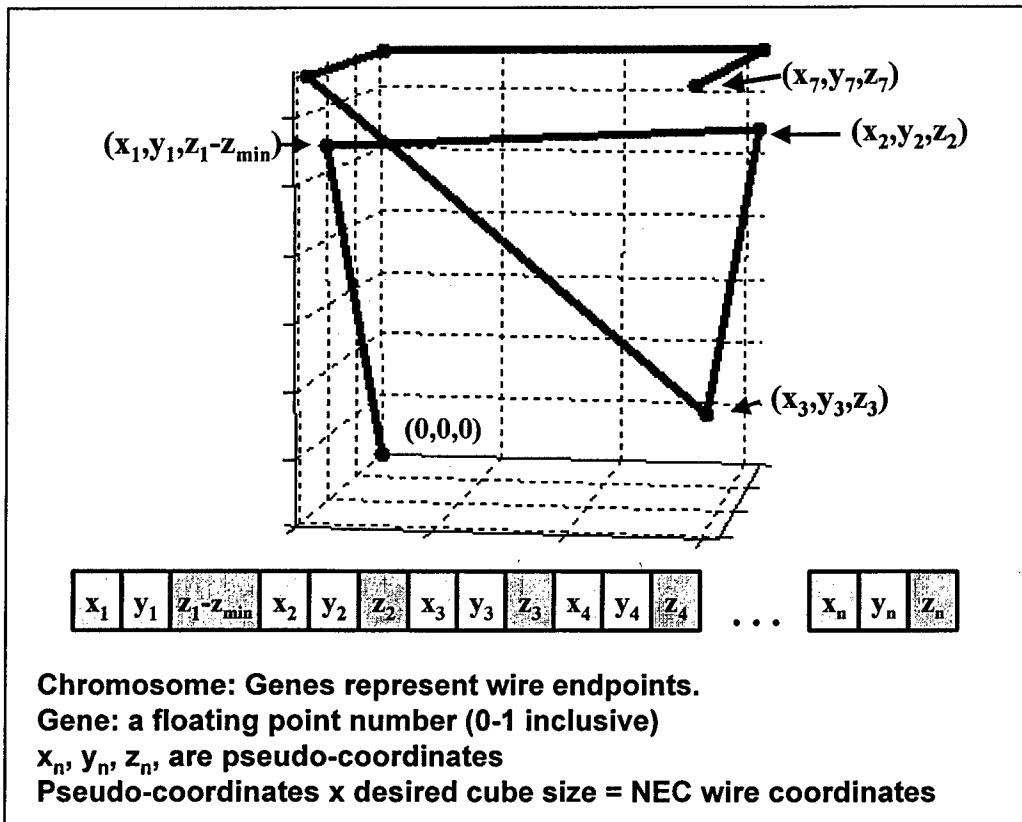**Pseudo-coordinates x desired cube size = NEC wire coordinates**

Figure 2. Coordinate-based genetic antenna chromosome and a typical resulting antenna.

endpoints (called "nodes"). The chromosome representation for this model then consists of a string of x, y, and z Cartesian-space coordinates for each of these nodes, as shown in Fig. 2. In the physical implementation of this chromosome, the nodes were originally coded using 5-bits for each coordinate [5]. However, in subsequent research, a real-valued GA was utilized and the coordinates represented by positive real values [1].

3.2 Angular Chromosome Representations

An alternative way to think of this problem is to model the antenna as a single piece of wire, subdivided into many fixed-length straight segments. The chromosome representation of an antenna would then be the angular orientation of each segment.

It is immediately obvious that there are two ways to represent these angular orientations. In the first sub-model, shown in Fig 3., we can represent them in an *absolute* fixed cylindrical coordinate system. In the second sub-model, the
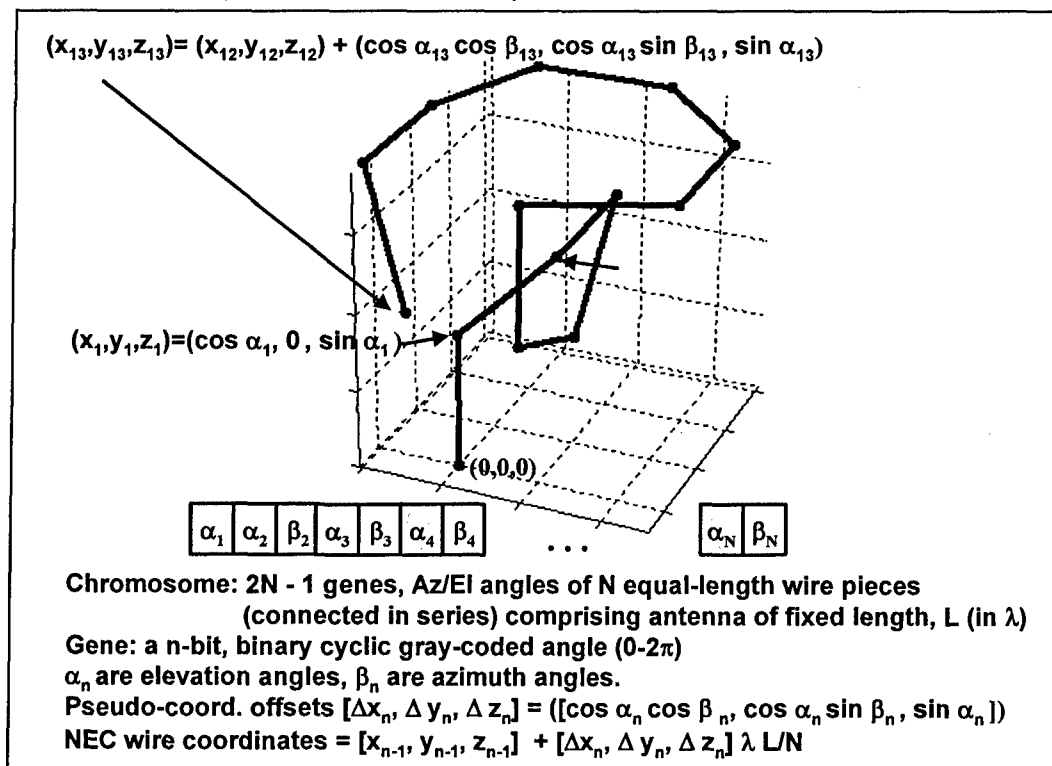

$$(x_{13}, y_{13}, z_{13}) = (x_{12}, y_{12}, z_{12}) + (\cos \alpha_{13} \cos \beta_{13}, \cos \alpha_{13} \sin \beta_{13}, \sin \alpha_{13})$$

$$(x_1, y_1, z_1) = (\cos \alpha_1, 0, \sin \alpha_1)$$

(0,0,0)

| α_1 | α_2 | β_2 | α_3 | β_3 | α_4 | β_4 | | α_N | β_N |

Chromosome: 2N - 1 genes, Az/El angles of N equal-length wire pieces
(connected in series) comprising antenna of fixed length, L (in λ)
Gene: a n-bit, binary cyclic gray-coded angle (0-2π)
α_n are elevation angles, β_n are azimuth angles.
Pseudo-coord. offsets $[\Delta x_n, \Delta y_n, \Delta z_n] = ([\cos \alpha_n \cos \beta_n, \cos \alpha_n \sin \beta_n, \sin \alpha_n])$
NEC wire coordinates = $[x_{n-1}, y_{n-1}, z_{n-1}] + [\Delta x_n, \Delta y_n, \Delta z_n] \lambda$ L/N

Figure 3. The absolute angle genetic antenna chromosome and a typical resulting antenna.

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$(x_{30}, y_{30}, z_{30}) = (x_{29}, y_{29}, z_{29}) + (\cos \alpha_{30} \cos \beta_{30},\ \cos \alpha_{30} \sin \beta_{30},\ \sin \alpha_{30})$

$(x_{2}, y_{2}, z_{2}) = (x_{1}, y_{1}, z_{1}) + (\cos \alpha_{2} \cos \beta_{2},\ \cos \alpha_{2} \sin \beta_{2},\ \sin \alpha_{2})$

$(x_{1}, y_{1}, z_{1}) = (\cos \alpha_{1},\ 0,\ \sin \alpha_{1})$

$(0, 0, 0)$

| $\Delta\alpha_1$ | $\Delta\alpha_2$ | $\Delta\beta_2$ | $\Delta\alpha_3$ | $\Delta\beta_3$ | $\Delta\alpha_4$ | $\Delta\beta_4$ | ... | $\Delta\alpha_N$ | $\Delta\beta_N$ |

Chromosome: 2N - 1 genes, representing Δ Az/El angles of N equal-length wire pieces (connected in series) comprising antenna of fixed length, L (in λ)
Gene: a n-bit, binary cyclic gray-coded angle (within +/- θ)
$\Delta \alpha_n$ are changes in elevation angle, $\Delta \beta_n$ are changes azimuth angles.
$\alpha_n = \alpha_{n-1} + \Delta\alpha_n \qquad \beta_n = \beta_{n-1} + \Delta\beta_n$
Pseudo-coord. offsets $[\Delta x_n,\ \Delta y_n,\ \Delta z_n] = ([\cos \alpha_n \cos \beta_n,\ \cos \alpha_n \sin \beta_n,\ \sin \alpha_n])$
NEC wire coordinates = $[x_{n-1},\ y_{n-1},\ z_{n-1}] + [\Delta x_n,\ \Delta y_n,\ \Delta z_n]\ \lambda\ L/N$

Figure 4. The relative angle genetic antenna chromosome and a typical resulting antenna.

orientations may be represented *relative* to a cylindrical coordinate system centered on the vector orientation of the previous wire segment, with the z-axis lying along the segment, shown in Fig. 4.[5]

There are intuitive pros and cons to each of these sub-models. Supporting the first representation, one might consider that the electrical properties of a wire segment have some strong relationship to it's orientation to the ground-plane (and hence to its mirror image). This would favor the absolute angle representation.

However, a counter argument follows the logic of what happens during genetic algorithm mating (or *recombination*), where a piece of one chromosome (or antenna) is merged with pieces of another parent chromosome to create children for the next generation. In such mating, the schema might be better preserved in

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[5] For both sub-models, the first azimuth angle was removed from the chromosome and fixed to be zero, to avoid competing identical solutions rotated around the z-axis. Also, for the relative angle chromosome, the first segment was represented relative to the z-axis of an initial reference frame.

the relative angle representation of the segments (relative to each other), rather than in absolute terms.

Rather than a real-valued chromosome, we encoded the angular chromosome representations into a cyclic gray-code binary representation. This has the benefit of allowing standard binary cross-over recombination operators, while eliminating the Hamming cliffs that occur in traditional binary representations. An additional benefit of a cyclic gray-code representation is the seamless cross-over in angular representation from the highest to the lowest values in this case from 2π back to 0.

3.3 Comparison of Chromosome Representations

We have illustrated three possible chromosome representations for the same antenna design problem. While a full discussion of the pros and cons of each approach has already been presented and may be found in [6], we provide a short summary here to illustrate the importance of good chromosome design.

First, not all of these representations are capable of representing all possible bent-wire antennas. In both the coordinate and angular chromosome representations, the number of straight wire pieces needs to be determined apriority. One could argue that if a sufficiently large number of small pieces were used, a general solution would be possible. However, experimentation showed that only the relative angle chromosome representation benefited from using many small pieces. The performance of both the coordinate and absolute angle chromosome representations deteriorated when the number of wire pieces or number of endpoint "nodes" exceeded a relatively small number (like 7-12 pieces). The relative angle representation, however, was successful with pieces as small as we were able to model with the limits imposed by the NEC thin-wire approximation methods. Hence this representation was best-able to model antennas closest to a general solution

Also notable is the fact that the angular representations require the antenna pieces to all be of equal-length and the total antenna length to be determined apriori, while the coordinate representation does not fix the length of the wire pieces or the total length of the antenna. These limitations could both be mitigated by expanding the angular chromosomes to include segment length information, which may be pursued in the future. However, note that the equal-length segments become only a very minor limitation when many very-small wire pieces are used: short pieces of antenna structure may be represented by only one or two of our short segments, while longer pieces are created by aligning the vectors many short segments to form one longer wire piece.
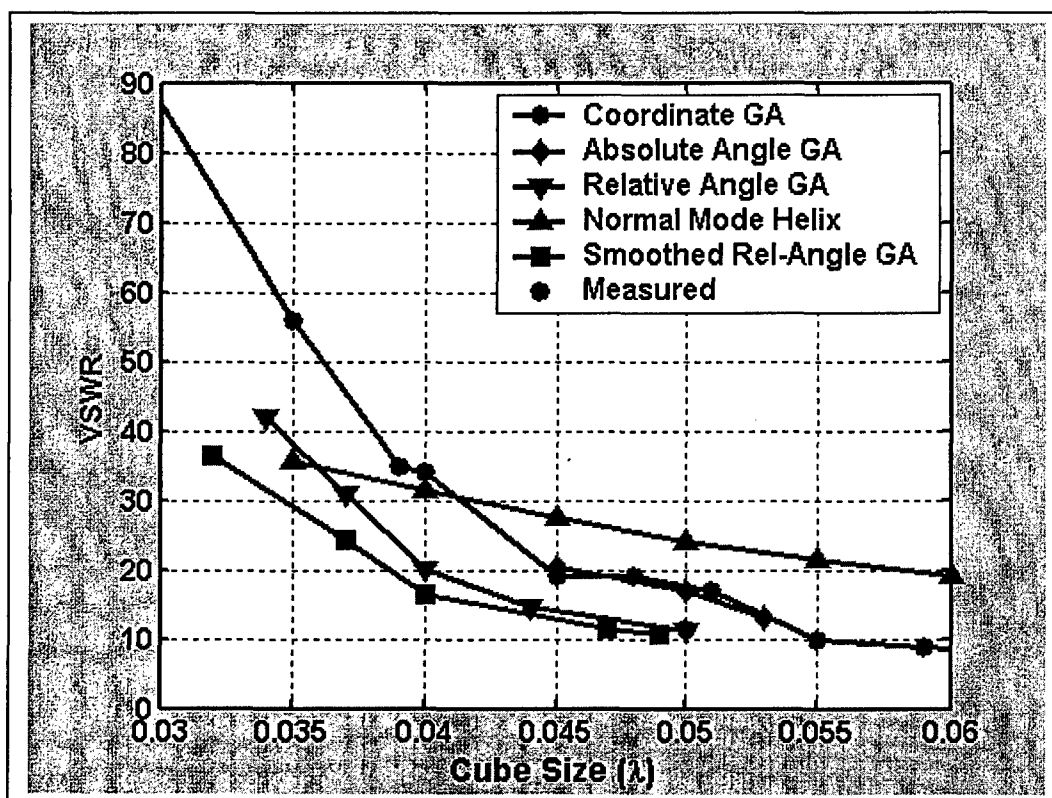
Figure 5: Comparison of lowest VSWRs obtained for a bent-wire antennas created by different chromosome representations for a desired cube size, of edge length λ.

Aside from the above discussion, other comparisons between and limitations of these three chromosomes can be made and are presented more completely in [6].

3.4 Results for Electrically-Small Bent Wire Chromosomes

In Fig. 5, we show results to date comparing antennas obtained using the coordinate, absolute-angle and relative-angle chromosomes. These results are more comprehensive than presently previous in [6], mainly because more GA runs have been completed.

We see that the absolute angle and coordinate chromosome representations performed similarly. The relative angle chromosome, using many small pieces, was able to create curving antenna structures which better met our criteria for low VSWR for a give cube-size. For comparison, we have included an electrically-

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small normal-mode helix on our curve. To date, only one of the antennas (the relative-angle solution for the .05λ cube-size) has been built and measured; however, the measured VSWR was as predicted by NEC.

We must point out that none of these antennas may represent the *optimal* single bent wire electrically small antenna for these cube sizes. As described earlier, all of these chromosomes limit the resulting antenna shape somewhat from a general solution. In fact, when the shapes resulting from the relative angle genetic algorithm design are "smoothed" by hand with no limitations on segment size or angle, even better results are achieved, as also shown in Fig. 5.

We hope that this discussion of chromosomes for the small antenna problem has provided a useful backdrop for illustrating the importance of chromosome representation. We now move on to discuss an antenna optimization problem we are also currently applying genetic algorithms to.

4. DISS Ionosonde Optimization

The Digital Ionospheric Sounding System (DISS) network is operated by the US Air Force Weather Agency (AFWA) in order to observe and specify the global ionosphere in real time. There are over a dozen fully automated digital ionosondes deployed worldwide to perform this function. Within the Air Force, the DISS network provides data for many products, including specification and forecasts of primary and secondary HF radio propagation characteristics, ionospheric electron density, and total electron content, ionospheric scintillation, environmental conditions for spacecraft anomalies, and sunspot number.

The system basically consists of a transmitting antenna that sends radio signals of different frequencies across a specified sweep (usually between 2 and 30 MHz) in a vertical direction that are then reflected, absorbed, or distorted by the ionosphere. Receive antennas then intercept the returning signals, for processing by various analysis algorithms.

The current transmitting antenna, an off-the-shelf model TCI-613F (shown schematically in Fig. 6a) was not designed for ionospheric measurements and does not exhibit the consistent gain in the vertical direction for all of the desired frequencies. We explored adding a standard log period array (LPA) antenna to the TCI (Fig. 6b); however, for the desired electromagnetic coverage, the resulting structure was mechanically difficult to deploy and maintain in isolated areas with extreme weather. We therefore began an investigation to determine if
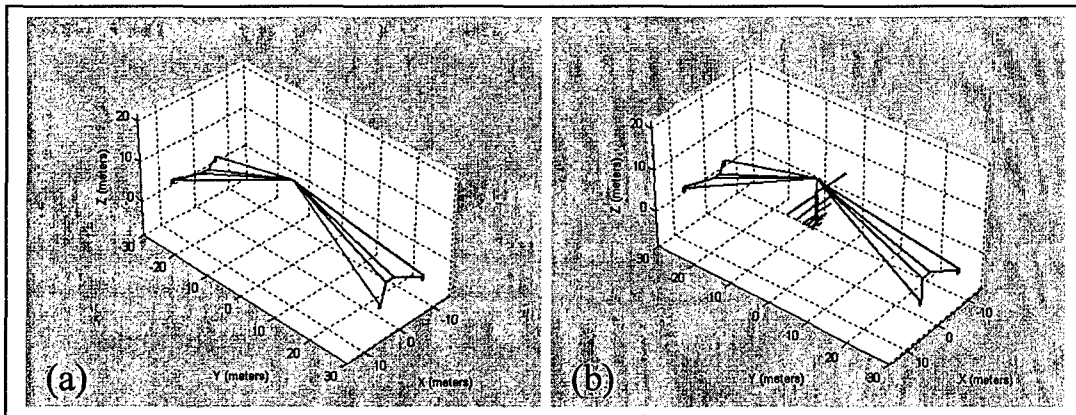
Figure 6: Schematic of TCI transmit antenna (a) and TCI with added LPA (b).

a modified antenna design could be optimized by a genetic algorithm for the DISS transmitting function.

4.1 Hybrid Folded-dipole / TCI Antenna Configuration

It was clear that we needed to add something resembling a log periodic array (LPA) or a folded dipole array to the TCI transmit antenna to provide additional frequency coverage. Since the mechanical structure of a standard LPA was unfeasible, we explored a folded wire design, using active elements folded down to additional ground stakes. We initially considered adding six parallel folded wires per side. However, since the addition of fourteen ground stakes per antenna was undesirable, we chose to modify the design to use only four additional stakes, two per side. This led to the hybrid antenna configuration shown in Fig. 7.

The hybrid antenna consists of some or all of the existing TCI antenna plus six pairs of new antenna wires. The wires are connected to the feed line, which runs up the tower, and are at various angles so that they may be mechanically connected to either part of the existing TCI curtain or two new ground stakes. Note that the entire length of each wire to the stake is not actively radiating – after the active length as been established, we transition to an insulator which then completes the mechanical connection.

The wires are currently arranged so that the highest new wire is connected out at an azimuth angle which allows it to be mechanically secured to the TCI curtain. The next two highest wires are connected to stake 1, with the lowest three wires are connected to stake 2.
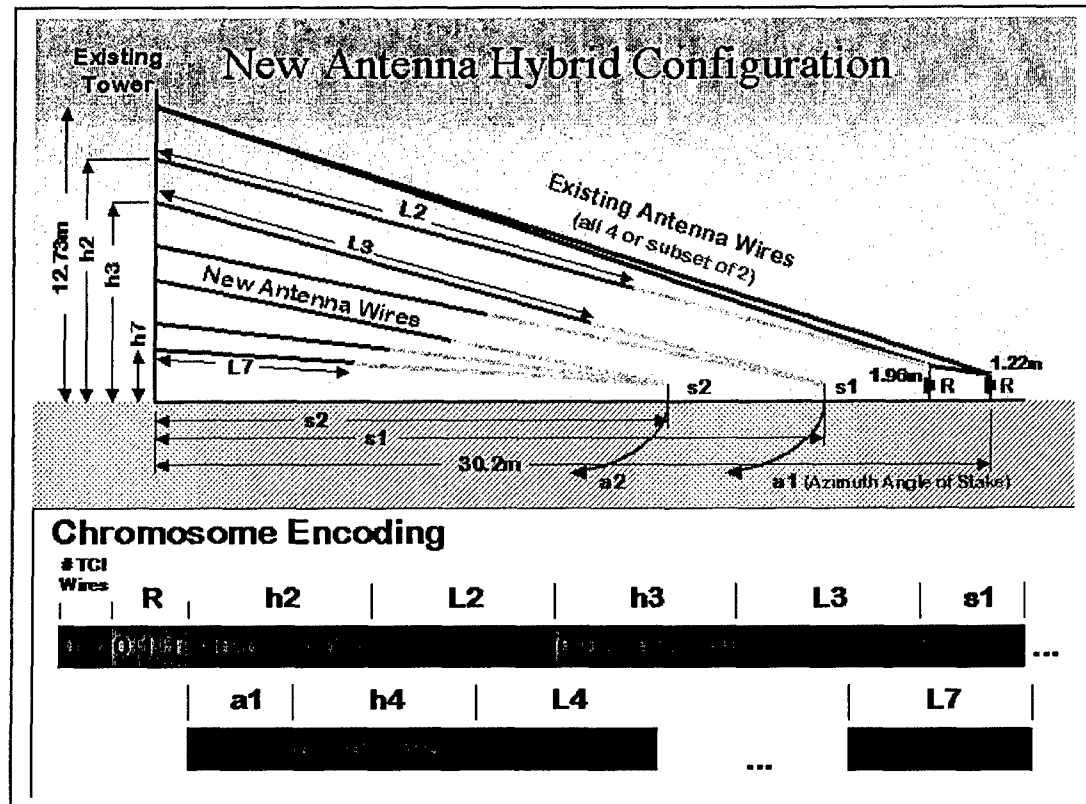
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Figure 7: Hybrid antenna, using some or all of the existing TCI antenna, plus seven pairs of wires running down to either the TCI curtain or two new stakes.

The distances of the stakes from the tower and their azimuth angles relative to the TCI antenna are variable and part of the optimization, as are the active lengths of each wire and the height of the wire on the tower.

This basic hybrid antenna shape was based on: 1) the realization that an LPA-like structure would be a beneficial addition to the TCI, and 2) mechanical, fabrication, and implementation constraints that required us to create a robust solution that was low-cost, easy to implement, and used as much of the existing system as possible. However, there were a number of parameters in this solution that needed to be optimized in order to achieve a satisfactory electromagnetic solution.

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4.2 Hybrid DISS Antenna Chromosome

As shown in Fig. 7, the chromosome we created to optimize this hybrid antenna design consists of a number of parameters. First of all, we were undecided on whether all the TCI wires (4 / side) were necessary or if the total antenna would be better if only a subset of the existing wires were used. Thus, the first 2-bit gene of the chromosome addresses these choices. The next gene of 3 bits addresses the value of the load resistance on the TCI antenna – it was initially 600Ω; however, we felt that it may need to be varied once the additional antenna structure was added.

Following this, we have genes addressing the heights and lengths of the six new wires (labeled L2 through L7[6]) and the two stake distances and azimuth angles (S1, A1, S2, and A2). The locations of these genes within the chromosome is somewhat important due to the necessity of keeping relevant genes together. For our current chromosome, we have embedded the stake distance and angle information for stake 1 (to which wires L3 and L4 connect) in-between the length and height genes for new wires 3 and 4. The angle and distance genes for stake 2 are located after the height/length genes for wire 5 (and before wires 6 and 7).

4.3 Figure of Merit

Our figure of merit for this optimization includes both an effective gain curve over the desired ionospheric measuring range from 2-30 MHz, and a desired VSWR (<= 3 when matched to 450Ω). We would ideally like a desired gain curve which is a constant 3dBi across our frequency range. However, given the reality of our lowest frequency (2MHz) and the physical area we are working in (within a 30 meter radius, roughly the existing footprint of the TCI antenna), we allow the desired gain curve to drop off somewhat at the low end, as shown in the graphs in Fig. 8. We may increase the desired gain curve at the low end in the future if we determine that our hybrid antenna design is capable of producing it.

Thus, our figure of merit, *FOM,* for this optimization consists of a weighted sum of the total effective gain error, Ge_{tot_err} (that which is less than our desired curve), the standard deviation of this error, $\overline{Ge}_{std\_err}$, the total VSWR error, $VSWR_{tot\_err}$ (that which is greater than 3) and the standard deviation of this error, $VSWR_{std\_err}$, such that:

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[6] We consider the TCI antenna wires to be an implicit "wire 1" in the antenna, thus starting our new wire labeling with wire 2, having length L2 and height on the tower of H2.

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$$FOM = Ge_{tot\_err} + 10 * Ge_{std\_err} + VSWR_{tot\_err} + 10 * VSWR_{std\_error} \qquad (1)$$

The standard deviation is important to avoid large error spikes in either effective gain or VSWR; however, it needs to be multiplied by 10 for it to have sufficient weight in the sum.

4.4 Initial Simulated Results for the Hybrid GA DISS Antenna

Our initial results using this chromosome to optimize the proposed hybrid DISS antenna using this figure of merit are extremely encouraging. Fig. 8a shows the effective gain and VSWR curves for the existing TCI antenna solution, simulated via NEC 4, and shown graphically in Fig. 6a. In Fig. 8b, we show similar curves that were obtained from simulations of the standard hybrid TCI / LPA solution shown earlier in Fig. 6b. In Fig. 9, we show one solution which has resulted from our genetic optimization of this hybrid folded-dipole design. While this is only a preliminary result, it shows that the genetic optimization was successful at using this chromosome to create an antenna which appears to be both mechanically
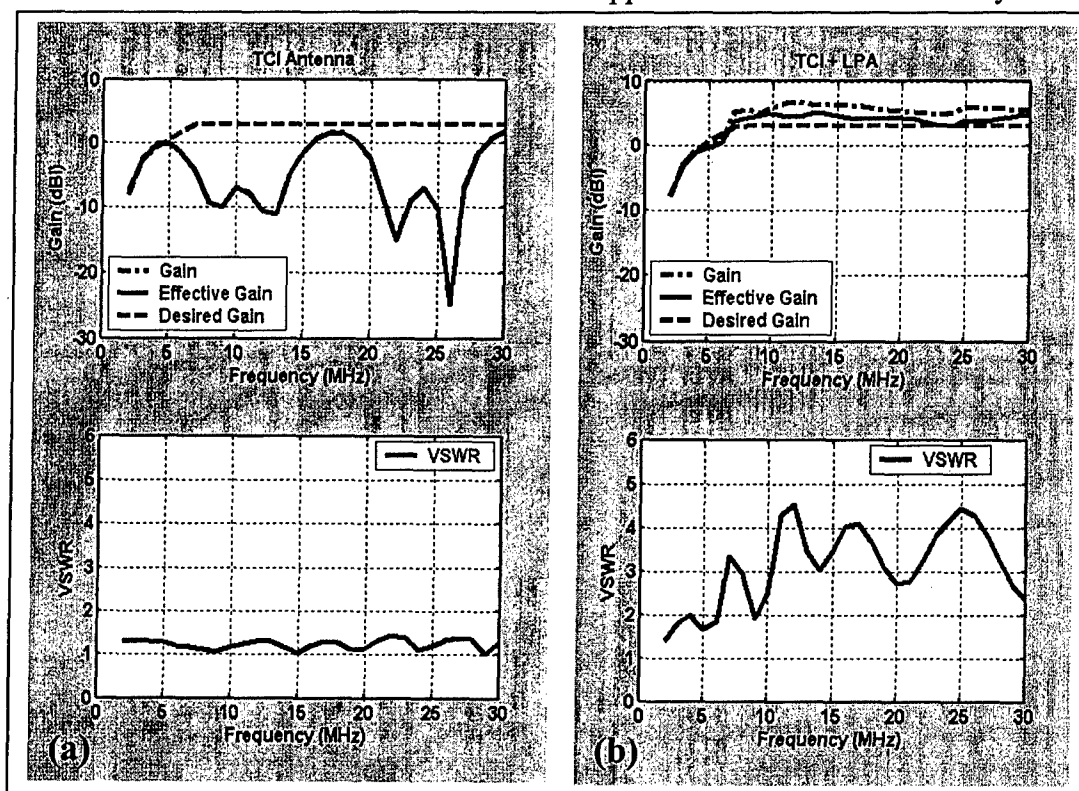
Figure 8: The modeled effective gain and VSWR of the existing TCI antenna (a) and the initial TCI+LPA configuration (b).
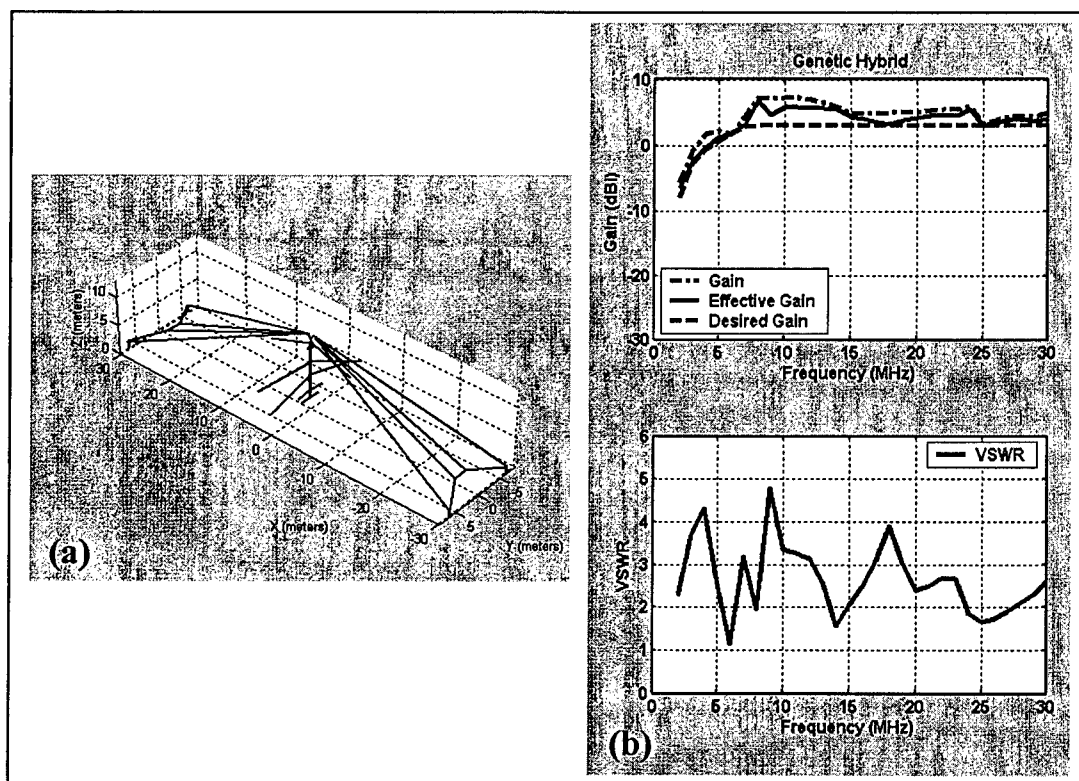
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Figure 9: A schematic representation (a) and the modeled effective gain and VSWR (b) of the Hybrid GA DISS antenna.

feasible for our environment while presenting fairly uniform gain across the desired bandwidth and a VSWR that (while not as good as the TCI alone) is similar to that of the TCI+LPA solution that was not mechanically suitable.

5. Conclusions

We have presented chromosome representations for two very different types of antenna designs and optimizations. For the electrically-small bent-wire antenna design, we illustrated how the problem could be modeled in three different ways, yielding three different chromosome encodings. Our optimizations for each of these show that some encodings were more effective than others. In the second example, we described how genetic algorithm optimization was applied to a hybrid digital ionosonde transmit antenna with a more complicated figure of merit. While this research is still on-going, our initial results indicate that genetic antenna optimization of this hybrid antenna design will yield an acceptable solution.

Our hope is that this paper and our experiences presented therein will be of use to you in analyzing your own antenna design or optimization problem and in creating a chromosome representation that is suitable and effective for genetic antenna optimization.

6. Acknowledgments

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